Assimilation of AIRS with Local Ensemble Transform Kalman Filter applied on the fvGCM

PROGRESS REPORT

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Outline

- Previous Results
  - Implemented LETKF on NASA fvGCM
  - Assimilate simulated grid point observations
- Current Results
  - Assimilate simulated rawinsonde observations
  - Comparison of PSAS and LETKF for perfect model
  - In spite of implementation challenges, LETKF obtains a superior analysis than PSAS
- Planned Experiments
  - Running experiments with real rawinsonde observations
  - Preparing to assimilate AIRS retrievals
  - Will assimilate AIRS radiances

NASA finite-volume GCM

The NASA finite-volume GCM(fvGCM) is a quasi-operational weather forecasting model.

It has 72 zonal, 46 meridional grid-points and 55 levels.

It has highly accurate numerics but it is very different from other models (e.g., surface pressure is not a prognostic variable)

Local Ensemble Transform Kalman Filter (LETKF, Hunt 2006)

- Forecast step

$$\mathbf{x}_i^f = m\mathbf{x}_{i-1}^a$$

$$\mathbf{P}_i^f = \mathbf{M}_{\mathbf{x}_{i-1}^a}\mathbf{P}_{i-1}^a\mathbf{M}_{\mathbf{x}_{i-1}^a}^T + \mathbf{Q}$$

- Analysis step

$$\mathbf{x}_i^a = \mathbf{x}_i^f + \mathbf{K}_i(\mathbf{y}_i^o - h(\mathbf{x}_i^f))$$

$$\mathbf{K}_i = \mathbf{P}_i^f\mathbf{H}^T[\mathbf{H}\mathbf{P}_i^f\mathbf{H}^T + \mathbf{R}]^{-1}$$

$$\mathbf{P}_{i\ n\times n}^a = [\mathbf{I} - \mathbf{K}_i\mathbf{H}]\mathbf{P}_i^f$$

- LETKF is an ensemble based Kalman Filter

$$\mathbf{P}_i \approx \frac{1}{k-1}\sum_{i=1}^{K}(x_i^f - \overline{x^f})(x_i^f - \overline{x^f})^T$$

$$= \frac{1}{k-1}\mathbf{X}^f \bullet \mathbf{X}^{fT}$$

- Do not require adjoint or Jacobian for the analysis

$$\mathbf{H}\mathbf{P}^f\mathbf{H}^\mathbf{T} \approx$$

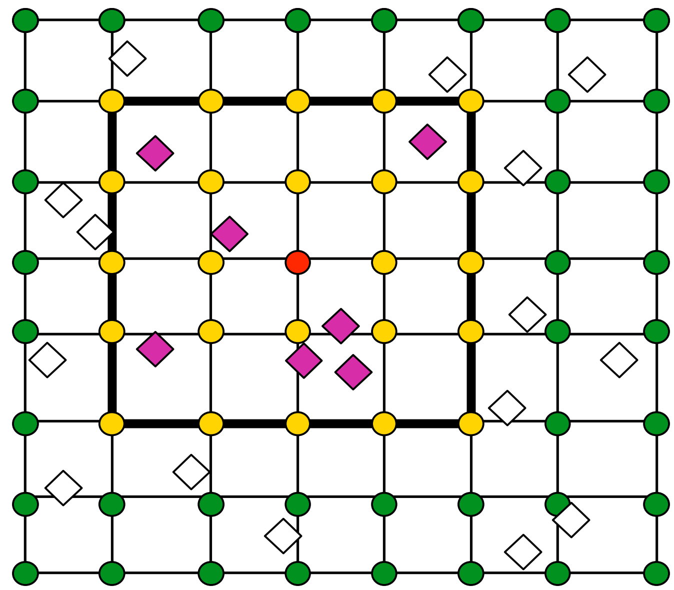
$$\frac{1}{k-1}\sum_{i=1}^{K}(h(x_i^f) - \overline{h(x^f)})(h(x_i^f) - \overline{h(x^f)})^T$$

Local Ensemble Transform Kalman Filter

Perform Data Assimilation in local patch (3D-window)

- The state estimate is updated at the central grid red dot

- All observations (purple diamonds) within the local region are assimilated



Advantages of LETKF

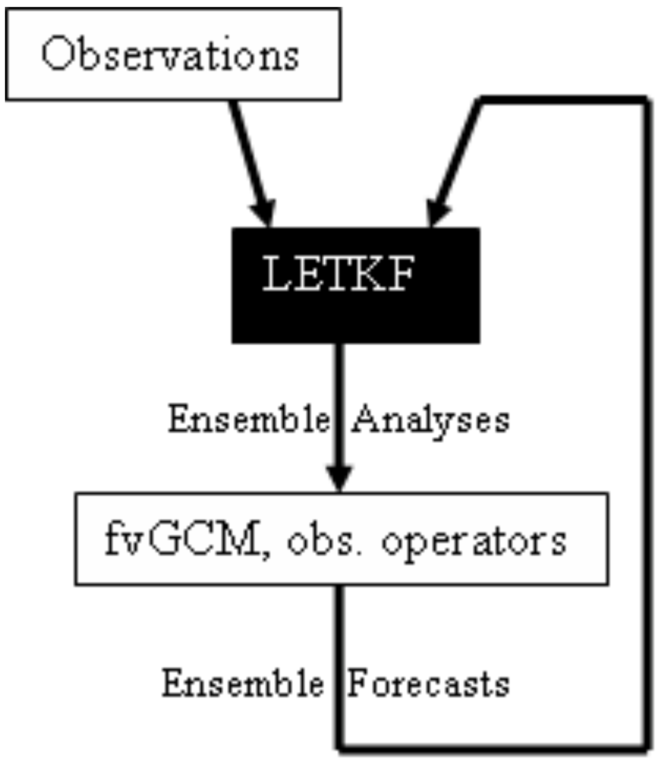
- Matrix computations are done in a very low-dimensional space: both accurate and efficient, needs small ensemble.

- The analysis is computed independently at each grid point, could be highly parallel!

- Very fast! 5 minutes in a 20 PC cluster with 40 ensemble members.

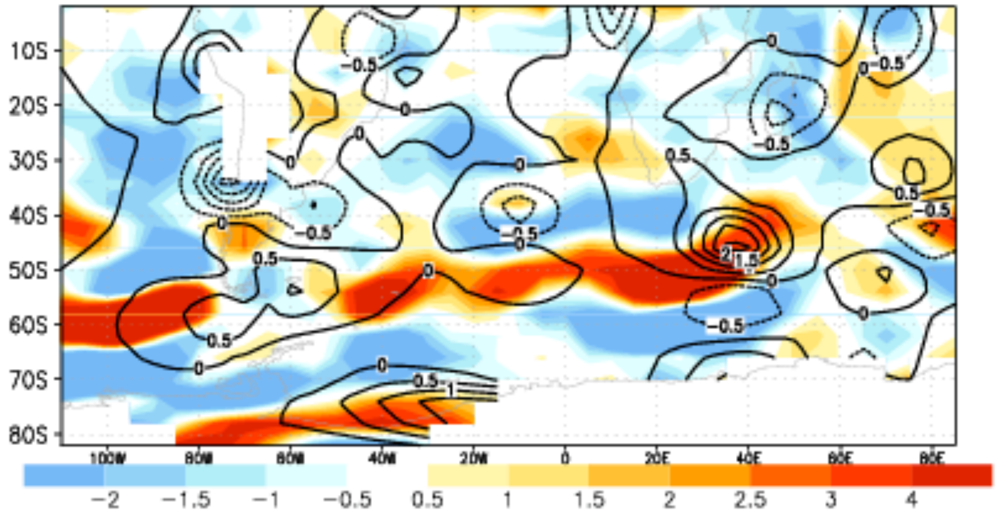
- Model independent, and also do not require adjoint of the model.

- It knows about the "errors of the day" through P^f.



Errors of the Day

PSAS



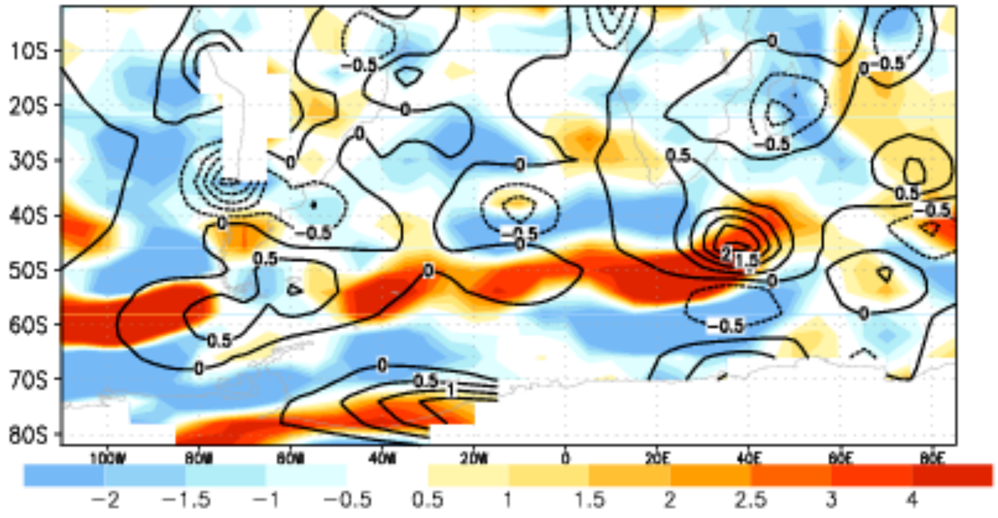
PSAS cannot account for the errors of the day!!

Snapshot of background error (colored area)

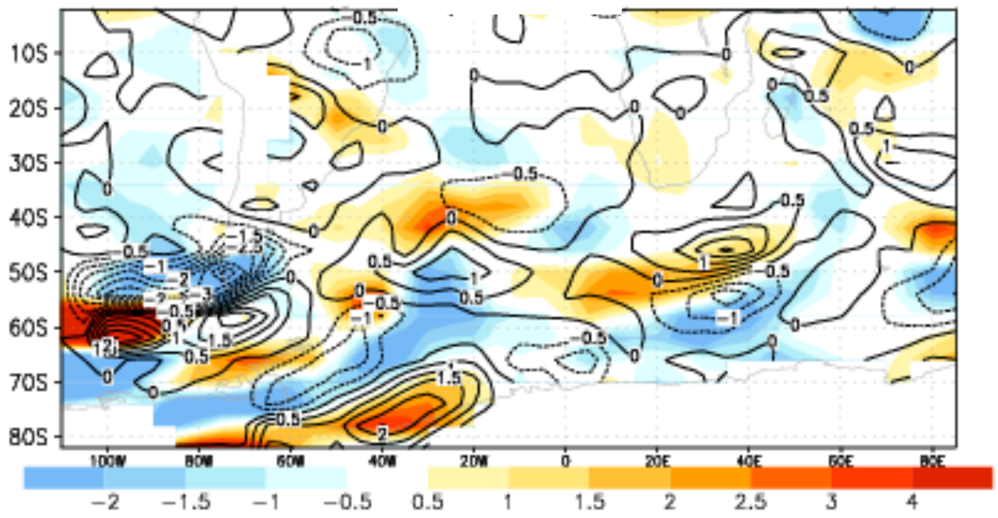
and analysis increment (contour)

Errors of the Day

PSAS



LETKF



PSAS cannot account for the errors of the day!!

LETKF does account for the errors of the day!!

LETKF Implementation Challenges

- Very limited computational resources (shared cluster of 20 PC's)
- Model has a very high top and strong instabilities at the top
- Must tune parameters of scheme
- Adaptation of existing forward operators to our scheme

Data Assimilation on NASA fvGCM with LETKF

Experimental Design:

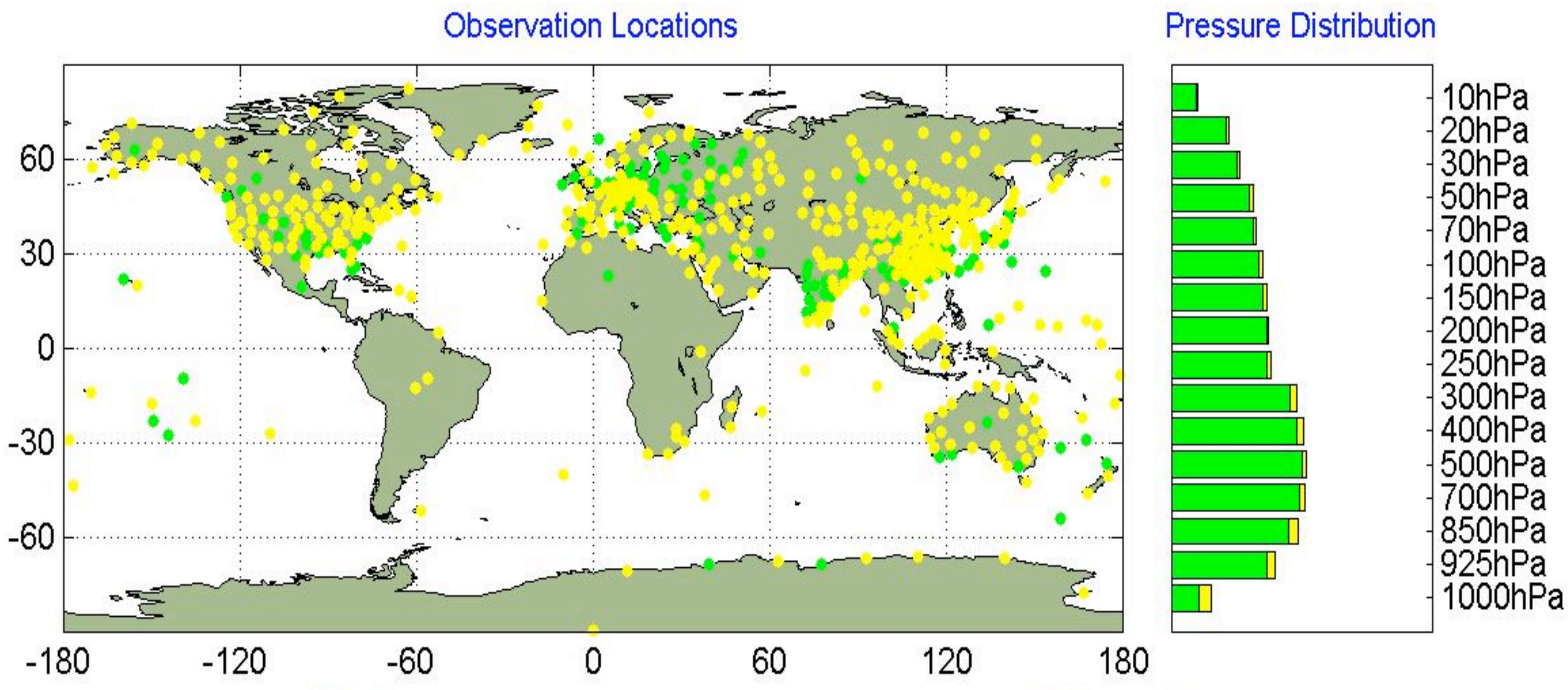
Perfect model scenario: A "true" trajectory is generated by integrating the fvGCM model for several months.

Simulated rawinsonde observations: The observations are the truth plus observational error as operational one. They are at rawinsonde locations. The observation types include: zonal wind(u), meridional wind (v), and geopotential height (H)

Inflation scheme : Multiplicative inflation is used.

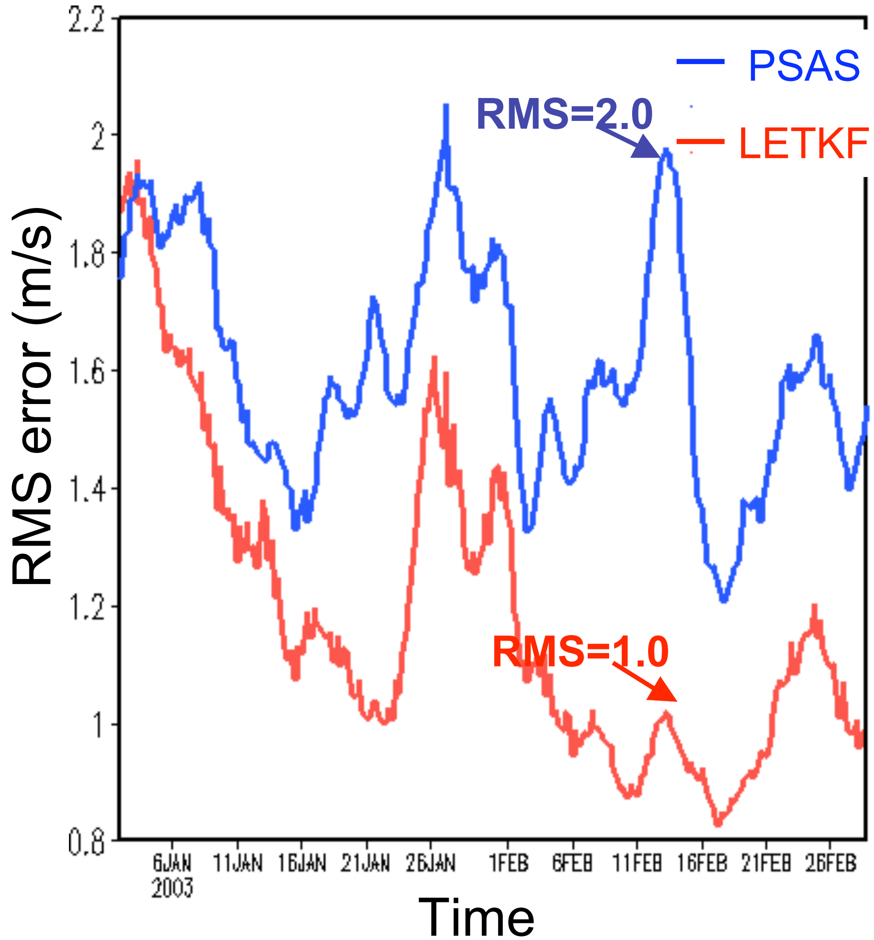
Local patch size : Change with latitude based on the observation coverage.

Real rawinsonde observation locations

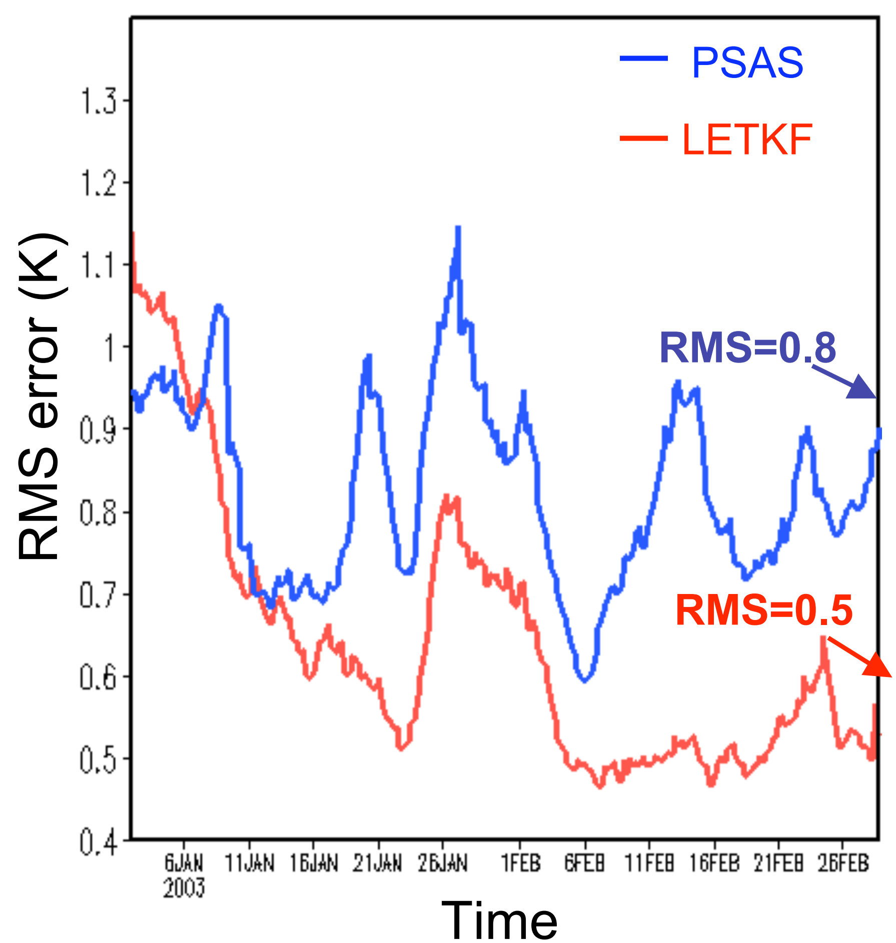


00Z rawinsonde observation distribution

500hPa analysis RMS error (Global average)

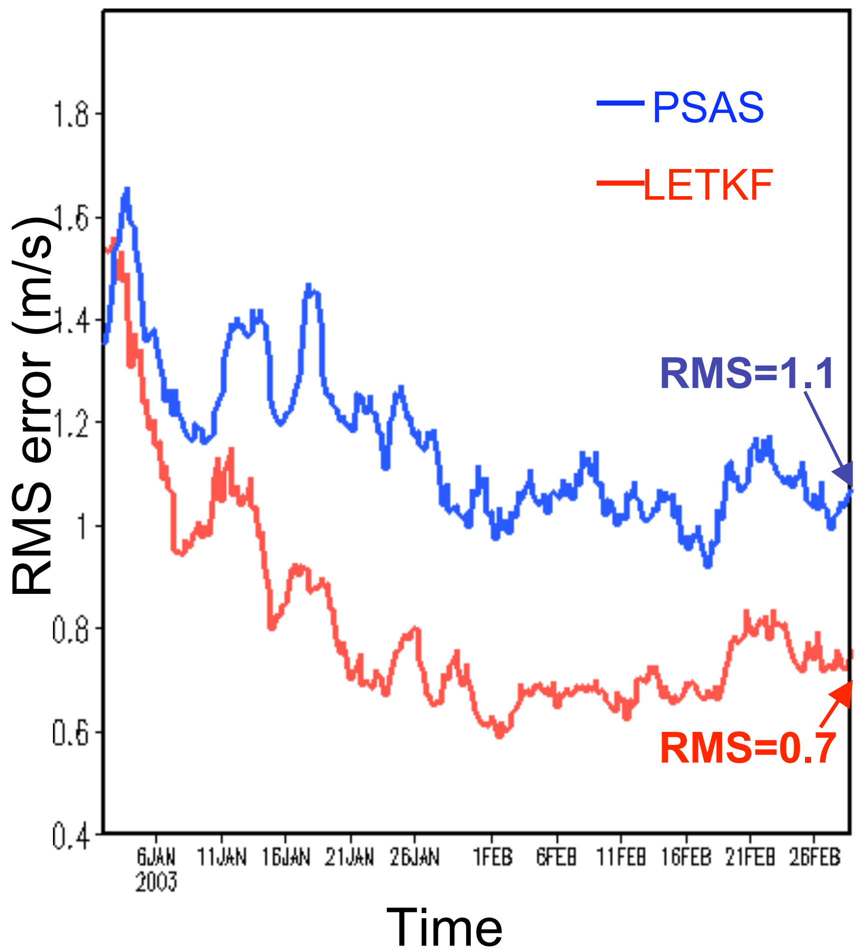


Zonal Wind

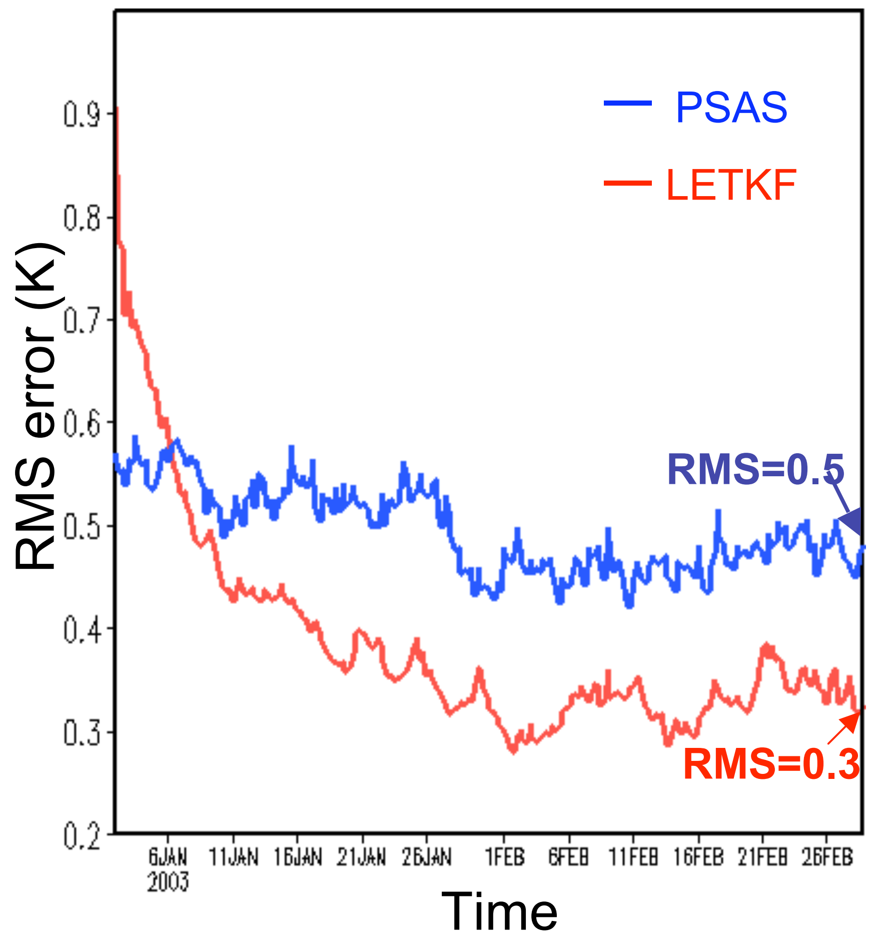


Temperature

500hPa analysis RMS error (Northern Hemisphere average)

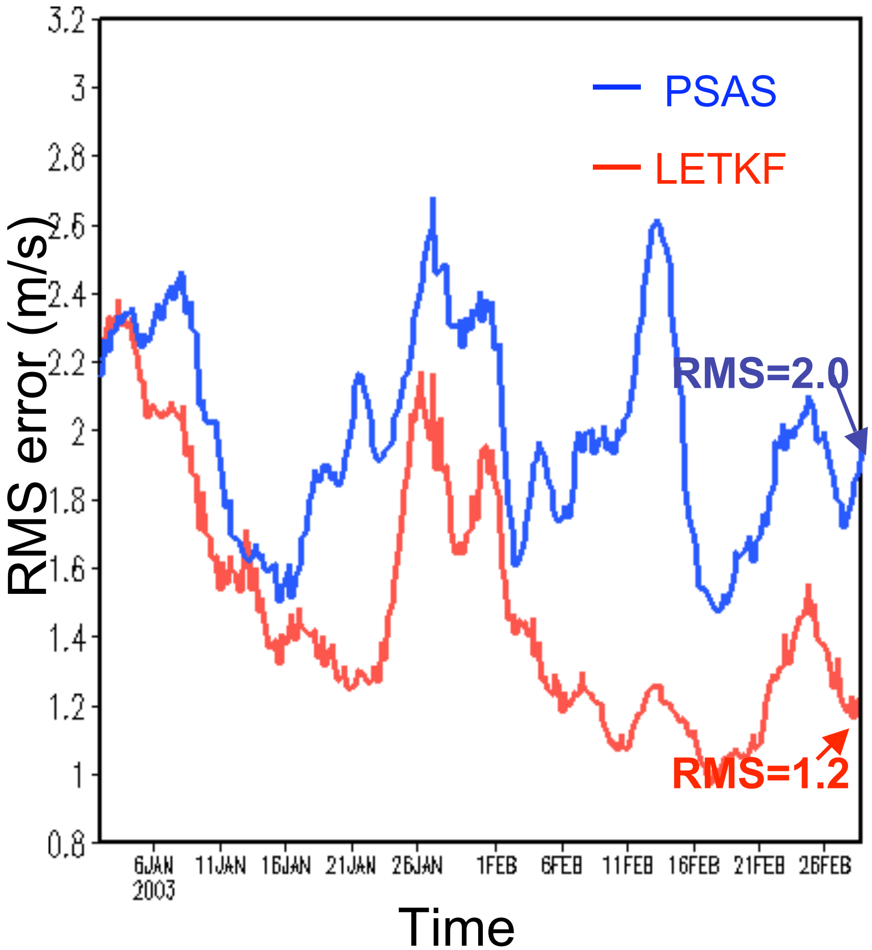


Zonal Wind

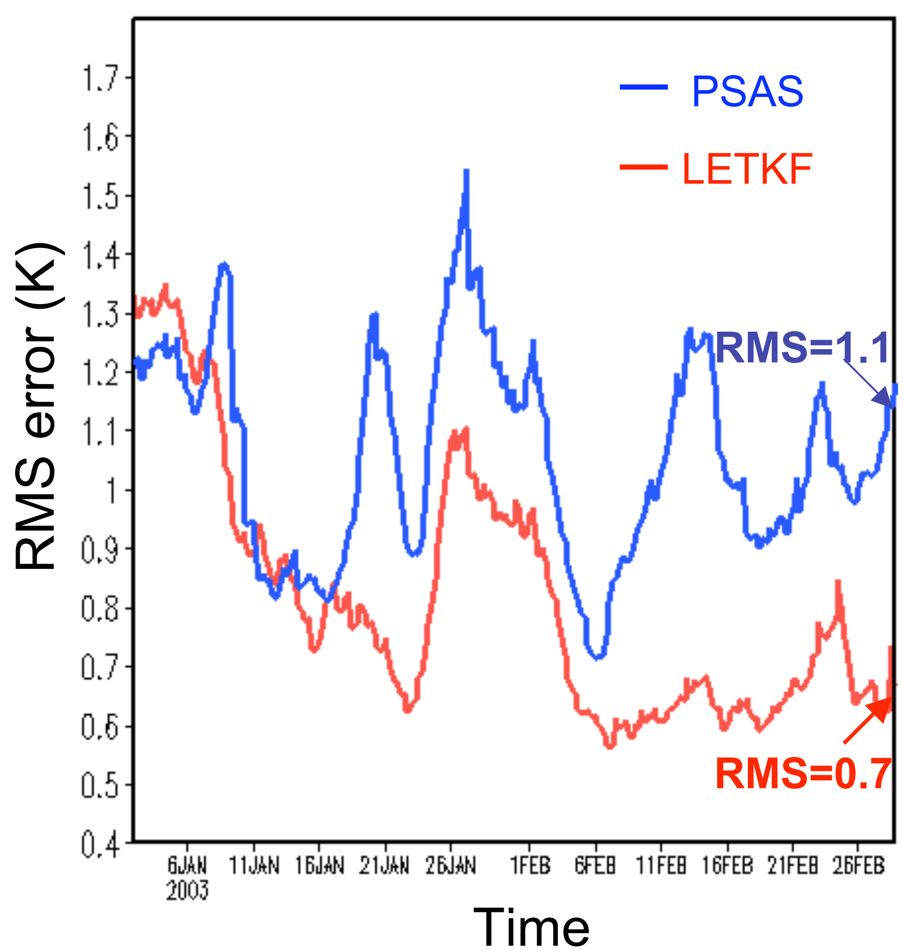


Temperature

500hPa analysis RMS error (Southern Hemisphere average)

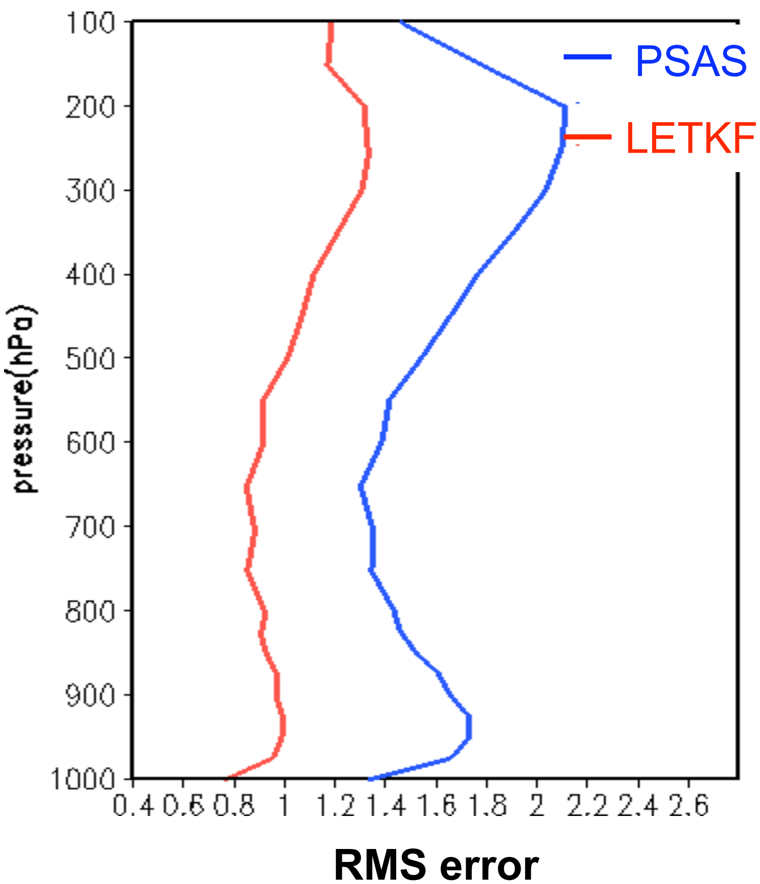


Zonal Wind

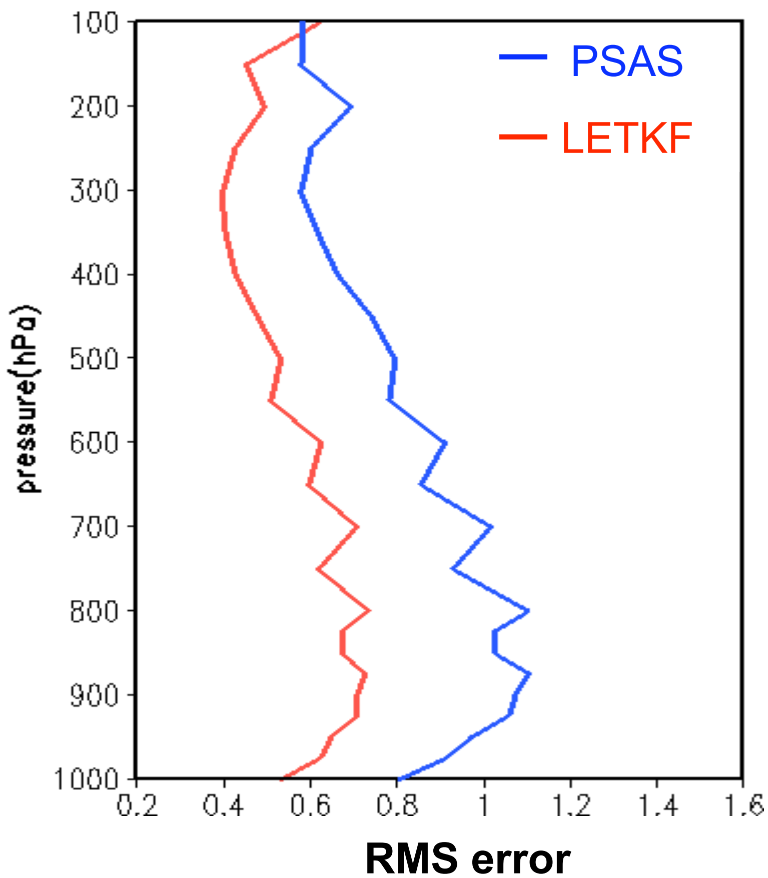


Temperature

Feb. average analysis RMS error at different levels (Global average)



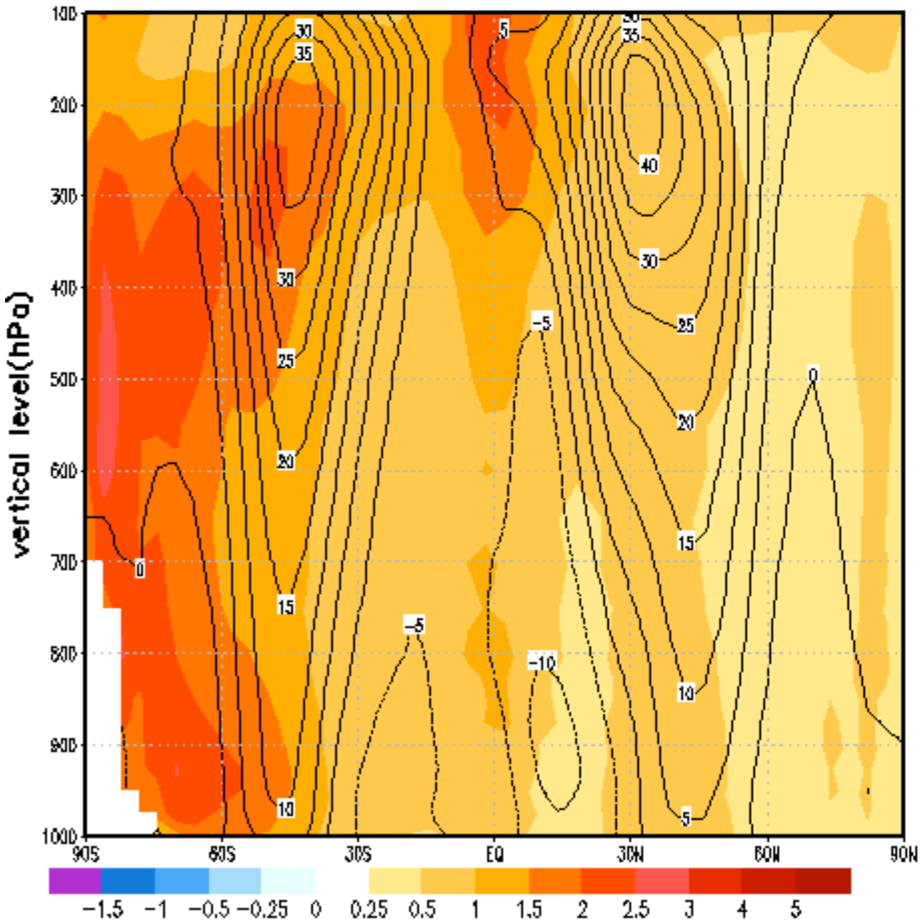
Zonal Wind



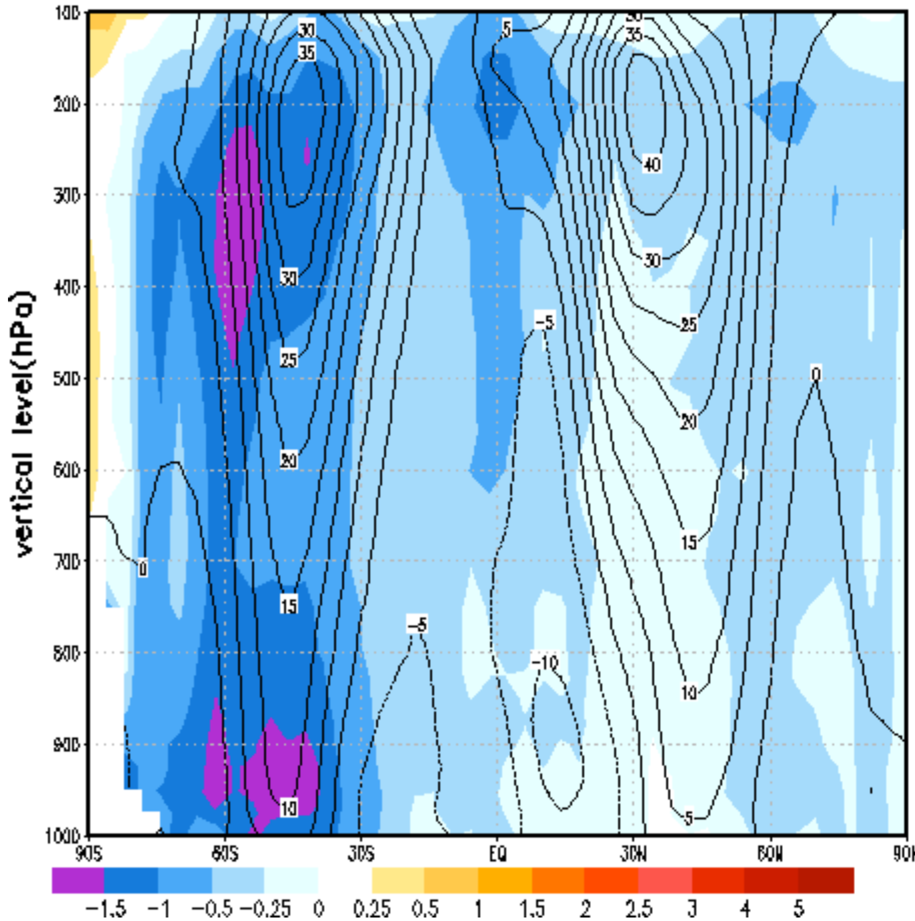
Temperature

Time mean of zonal mean analysis RMS error (averaged over February) and dynamical state (contour)

Zonal Wind



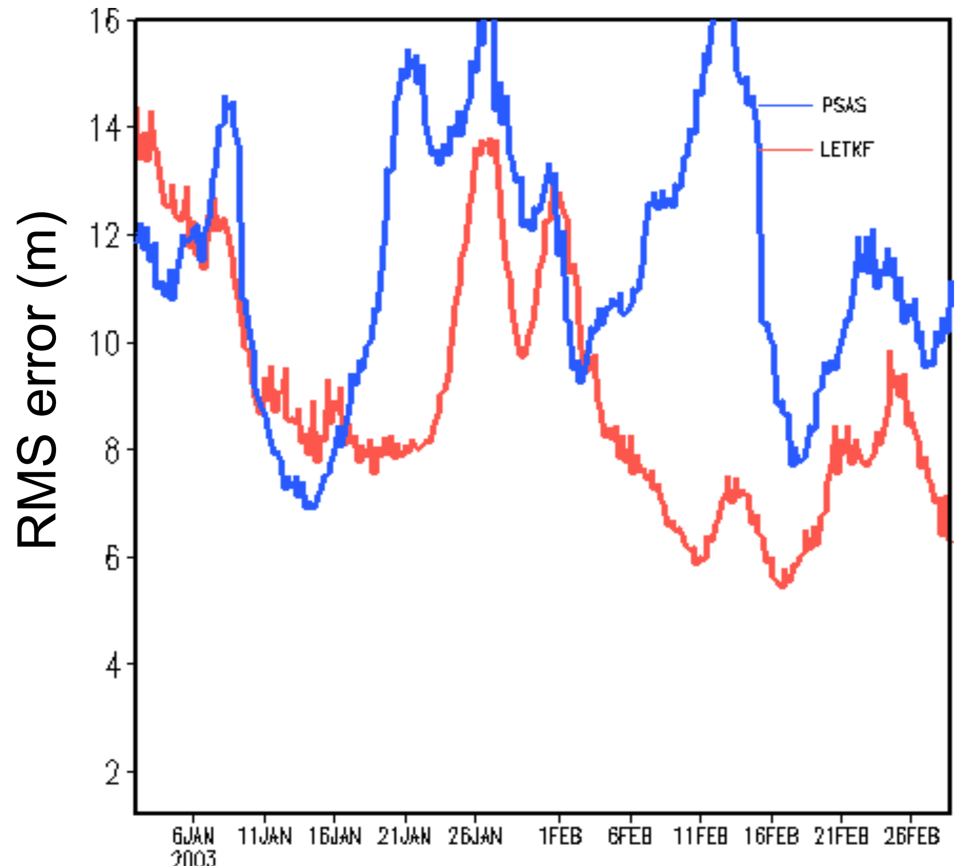
RMS error of LETKF

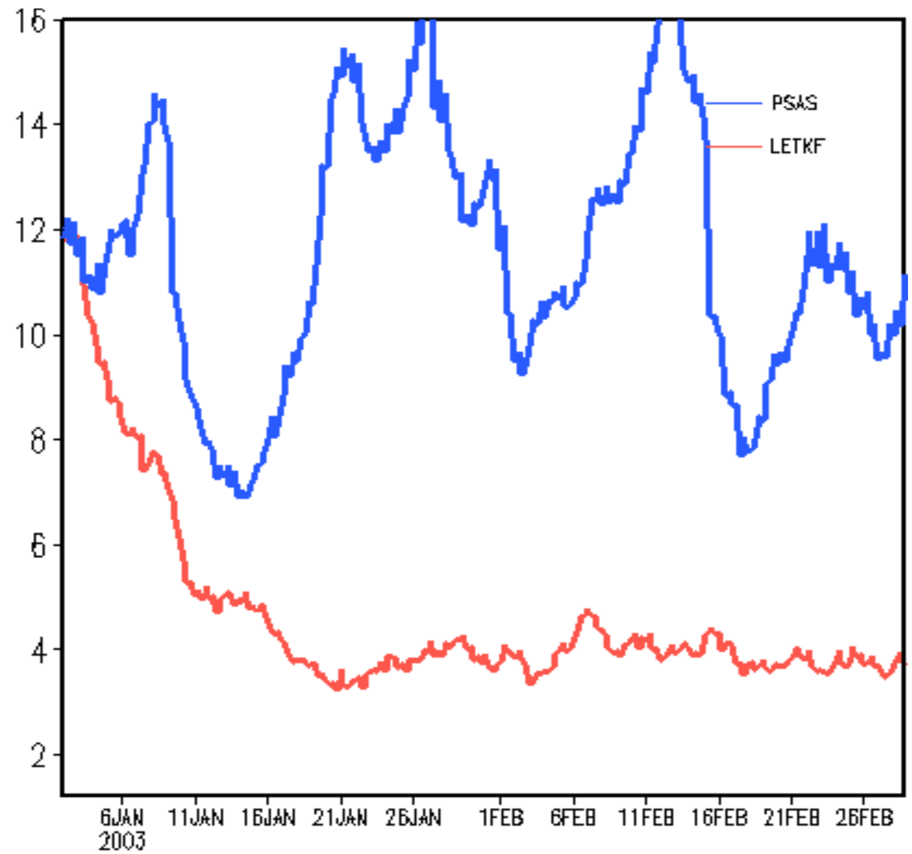


RMS error difference between LETKF and PSAS

Analysis RMS error (Global average): Solving a LETKF challenge

500 hPa Geopotential Height





Without updating del P

With updating del P

Conclusions

- For simulated rawinsonde observations, with operational possible ensemble member(40), LETKF is much better than NASA PSAS analyses after the spin-up time. The percentage improvement is up to 50% in Southern Hemisphere, most areas is between 30% and 40%.

- LETKF captures the error of the day, while PSAS cannot.

- LETKF is an efficient and parallel method of data assimilation. 5 minutes in a 20 PC cluster with 40 ensemble members.

- LETKF can use the nonlinear observation operator and does not require Jacobian or the adjoint. We can compare different nonlinear forward operators.

Starting now real observation experiments: first rawinsondes, then AIRS retrievals

Planned experiments:

1) *Real rawinsonde observations:* The observation types include: zonal wind (u), meridional wind (v), temperature (T), specific humidity (q), and sea level pressure (SLP).

2) *Add AIRS retrievals:* T, q with high density coverage

3) *Rawinsondes plus clear AIRS radiances:* This is more accurate but has fewer locations.

(Because we do not require the Jacobian and adjoint, we can use L. Strow's observation operator)

4) *AIRS data impact:* Compare analyses and forecasts to estimate the impact of AIRS alone.

Will have to optimize LETKF parameters

References and thanks:

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